#### A Deep Convolutional Neural Network for **OTHER TOTAL** Brain Tissue Segmentation in Neonatal MRI

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### Introduction



Brain tissue segmentation is a prerequisite for many subsequent. The trained network was used to segment tissue types on a automatic quantitative analysis techniques. As with many medical further 5 axial T2-weighted scans which are provided by the imaging tasks, a shortage of manually annotated training data is a neobrains12 public challenge[1]. Evaluation was performed limiting factor which is not easily overcome, particularly using recent independently by the challenge organisers and the reference deep-learning technology. We present a deep convolutional neural standard is never seen by participants. Compared to other network (CNN) trained on just 2 publicly available manually annotated participating algorithms, our method obtained the highest volumes, trained to annotate 8 tissue types in neonatal T2 MRI. The median Dice Coefficient across various tissue types (figure 3). network makes use of several recent deep-learning techniques as well The median value for Mean-Surface-Distance was second as artificial augmentation of the training data, to achieve state-of-the- highest, being surpassed only by a participant who had art results on public challenge data.

access to additional related training data. Figure 4 shows sample results on test data from the challenge.

## Method

A fully convolutional neural network (see figure 1) with a total of 11 layers is trained to map T2-weighted images to tissue segmentations. The training data consists of just 2 axial volumes, available publicly via the neobrains12 challenge[1]. Eight different tissue-types are segmented as illustrated in figure 3 (Results).







Figure 1: (a) A schematic drawing of a fully convolutional neural network with T2-weighted MRI as input and segmentation data as output. (b) A numerical demonstration of how a convolution with input values (blue) with weights (yellow) results in output (green). (c) An illustration of how dilated convolution spans a larger region at no additional computational expense.

Training data is augmented by applying a number of random perturbations to every slice extracted during training, as shown in figure 2. This allows the network to learn variations which may not be present in the limited training data



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**Figure 3:** Plots showing how the presented method (left) performs against comparable methods in the neobrains12 challenge[1] in terms of Dice Coefficient for overlap. Coloured points show mean performance for each tissue type, while box-plots summarise this data. \*\*Indicates participants with access to related additional data



Figure 4: Sample network segmentation results on neobrains12 [1] test data. Tissues are cerebellum (orange), cortex (darkest blue), white-matter (lightest blue), cerebro-spinal fluid (dark red), ventricles (light red), brain-stem (yellow), basal-ganglia/thalamus (mid blue), *myelination (light green)* 

(colour) ratio Figure 2: A demonstration of how training data is augmented by adding subtle random variations to the original data.

Network technical details: The network uses batch-normalization, dilated convolutions and stacked residual layers. The Adam optimizer is used and loss is calculated by cross-entropy.

#### Contact References 1. neobrains12.isi.uu.nl keelin.murphy@ucc.ie Isgum et al, Evaluation of automatic neonatal brain segmentation algorithms: The NeoBrainS12 challenge, Medical Image Analysis, 2015.

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## Conclusion

Deep learning using the appropriate network architecture and data augmentation techniques have enabled state-ofthe-art segmentation results using minimal training data. The presented method performs better than others which had access to additional related training scans. This is a promising result for deep learning in the medical imaging domain where a shortage of training data is typically a significant issue.



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